



D1.14: Best Practices in Developing Open Platforms for Agri-food Robotics – updated final version

**WP1 – Competence Centers and Technical Expertise
Management**

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 825395

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Document Information

G.A. No.	825395	Acronym	agROBOfood
Full Title	Business-Oriented Support to the European Robotics and Agrifood Sector, towards a network of Digital Innovation Hubs in Robotics		
Horizon 2020 Call	DT-ICT-02-2018: Robotics - Digital Innovation Hubs (DIH)		
Type of Action	Innovation Action		
Start Date	1 st June 2019	Duration	48 months



Project URL	https://agrobofood.eu/			
Document URL	-			
EU Project Officer	Jan Hückmann			
Project Coordinator	Kees Lokhorst			
Deliverable	D1.15: Best Practices in Developing Open Platform for Agri-food Robotics			
Work Package	WP1 – Competence Centers and Technical Expertise Management			
Date of Delivery	Contractual	M30	Actual	M30
Nature	R – Report	Dissemination Level		Public
Lead Beneficiary	Delft University of Technology (TU Delft)			
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Reviewer(s)	Erik Pekkeriet (WR), Christoph Hellmann Santos (Fraunhofer)			
Keywords	Best practices, open-source			

Document History

Version	Issue Date	Stage	Changes	Contributor
1.0	21 May 2020	Draft	First draft	TU Delft
1.1	23 May 2020	Draft	Incorporation of comments from partners	Fraunhofer IPA, CEMA, INES TEC
1.2	27 May 2020	Draft	Refinements	TU Delft
1.3	29 May 2020	Draft	Final draft D1.15	TU Delft
2.0	31 May 2020	Final	Minor adjustments to D1.15	TU Delft
3.0	11 Nov 2021	Draft	D1.14 Updated version with newly added Chapter 2 and Section 5.1 to address reviewer comments.	TU Delft
Final	3 Dec 2021	Final		TU Delft



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1 Introduction

This document is written for readers with an interest in agricultural robotics. Although robotics is not commonplace yet in the field of agriculture, there are already so many past and ongoing projects and products that it is difficult to decide where to start. What are the best practices to build upon? This document contains up-to-date overviews of potential examples as well as suggestions for best practices that can be used as a solid base for further developments.

As cited from a recent review paper [122], "practical agriculture robots rely not only on advances in robotics, but also on the presence of a support infrastructure. This infrastructure encompasses all services and technologies needed by agriculture robots while in operation, this include a reliable wireless connection, an effective framework for Human Robot Interaction (HRI) between robots and agriculture workers, and a framework for software sharing and re-use". This statement is captured in the schematic representation in Fig. 1. Apparently, an integrated framework for software/hardware for agricultural robotics domain has not yet been in place, as there are lots of existing tools out there. However, lots of agricultural robotics problems may not use the best tools to solve them or are not aware of some tools. So listing and analyzing the existing open software/hardware tools will help improve the performance of common agricultural robotics problems.

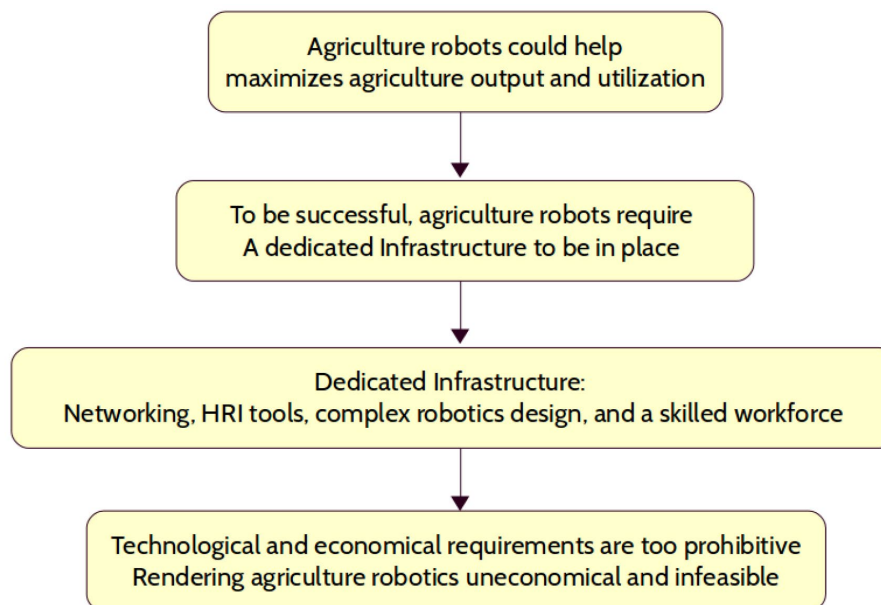


Fig 1: Schematic representation of the challenge of implementing agricultural robotics. From [122].

This document is a "live" document which will receive updates throughout the project. It is intended as a stand-alone document that can be used for a quick-jump into the state of the art of agriculture robotics. Nevertheless, it is part of a Europe-wide endeavor which is the agROBOfood project, which intends to connect all of Europe's many high-quality projects on agriculture robotics. The following list of ongoing projects is taken from the EuRobotics Multi-Annual Roadmap on Robotics [97]:

- HUBRINA (HUMAN-roBOT co-WORKING IN Agricultural master-slave systems)
- ECHORD. Master-slave robot control for agricultural activities.
- FutureFarm
- ERA-NET ICT Agri. Typify current and new robot technology and their potential tasks in farming.
- CROPS (Clever Robots for Crops)
- ERA-NET ICT Agri. Intelligent sensing and manipulation for sustainable production and harvesting of high value crops

- RHEA (Robot Fleets for Highly Effective Agriculture and Forestry management)
- ERA-NET ICT Agri. Design, development, and testing of a new generation of automatic and robotic systems for both chemical and physical –mechanical and thermal– effective weed management focused on both agriculture and forestry.
- GEOPAL (GNSS-based Planning system for Agricultural Logistics)
- QUAD-AV (Ambient Awareness for Autonomous Agricultural Vehicles)
- ERA-NET ICT Agri. Enhancing SafetyLevel of autonomous agricultural vehicles during process in terms of threats to humans, animals and tangible goods.
- SmartBot - (here: Subproject AgroBot)
- INTERREG. Develop basic technologies needed for constructing multiple, agriculture, robotic demonstration models with different application
- Robs4Crops – bringing the farmer perspective to agricultural robotics

This document focuses on mobile ground-based robotic systems. Interesting topics not included in this document are aerial robotics as well as fixed (non-mobile) ground-based systems that operate on conveyor belts or move as large CNC machines [124]. Furthermore, due to the abundant availability of research project information as opposed to commercially available solutions, this is overrepresented in the current version of the document.

The content is distributed of the next chapters in the following way. Chapter 2 selects the best candidate overall software framework, Chapter 3 focuses on the technological best practices within that framework, and Chapter 4 focuses slightly more on organizational aspects, yet still firmly connected to the robot technologies.



2 Best Robotics Software Framework

The first step toward the recommendation of the best specific practices for Agricultural robots is to make a well-informed choice regarding the overall software framework to use. We have done a comparative study which concludes that currently ROS is the best practice. The detailed analysis is given in this chapter. That conclusion is the basis for the selection of more specific information in Chapters 3 and 4.

2.1 Robotics frameworks and middleware's

Agricultural robots are complex systems. Typically many different processes need to run concurrently, such as navigation, perception, manipulation and process and mission control. Enabling this in a software system while keeping the software modular and well-structured calls for a programming framework including middleware.

There are a number of open source programming and middle ware frameworks available for robotics that have reached product readiness. The most common middleware frameworks in robotics, which will be analysed in the following sections, are:

1. **ROS** - The Robot Operating System
2. **ROS2** - The Robot Operating System2
3. **YARP** - Yet Another Robot Platform
4. **ROCK** - The Robot Construction Kit
5. **Orocos** - Open Robot Control Software

2.2 The Robot Operating System

The Robot Operating System is probably the best known open source software development kit for robotics. It is proven in use and already in many robot products. Today, more than 80k developers have used ROS for building software on Github.



2.2.1 Notable Features

- High quality ecosystem packages for navigation, manipulation, perception and simulation
- Integration with a large number of robots (industrial, service and automobile)
- Bridges to all other robot programming frameworks and middleware's mentioned here



2.2.2 Related links

Reference type	Link
Documentation	http://wiki.ros.org/Documentation
Support	https://answers.ros.org/questions/
Core Repositories	https://github.com/ros
Package Index	https://index.ros.org/
Governance Organization	https://www.openrobotics.org/
Supporting Initiatives	https://www.autoware.org/ , https://rosindustrial.org/

2.3 The Robot Operating System 2

ROS also has a second version, that is being developed by major companies and is cut towards industrial usage. ROS2 is definitively the future of robotics software development. The first stable release is from June 2020 and the package ecosystem is growing.



2.3.1 Main Target Systems

- Service robots (PR2, Care-O-Bot 3+4,...)
- Industrial robots (Yaskawa, UR, Pilz, Techman, Doosan, ...)

2.3.2 Notable Features

- High quality ecosystem packages for navigation, manipulation, perception and simulation
- Real-time capabilities and development lead by Technical Steering Committee
- Bridges to all other robot programming frameworks and middleware's mentioned here



2.3.3 Related links

Reference type	Link
Documentation	https://docs.ros.org/en/foxy/index.html
Support	https://answers.ros.org/questions/
Core Repositories	https://github.com/ros2
Package Index	https://index.ros.org/
Governance Organization	https://www.openrobotics.org/
Supporting Initiatives	https://www.autoware.org/ , https://rosindustrial.org/

2.4 YARP (“Yet Another Robot Platform”)

YARP supports building a robot control system as a collection of programs communicating in a peer-to-peer way, with an extensible family of connection types (tcp, udp, multicast, local, MPI, mjpg-over-http, XML/RPC, tcpres, ...) that can be swapped in and out to match your needs.



2.4.1 Main Target Systems

- Humanoid robots (I-Cub)

2.4.2 Notable Features

- Support for Linux & Windows
- Legged robot support through whole body controller
- Driver support for a number sensors and actuators

2.4.3 Related links

Reference type	Link
Documentation	http://www.yarp.it/git-master/index.html
Support (for)	https://github.com/robotology/icub-tech-support
Core Repositories	https://github.com/robotology
Package Index	https://github.com/robotology/robotology-superbuild
Governance Organization	https://www.iit.it/web/guest
Supporting Initiatives	https://icub.iit.it/

2.5 The Robot Construction Kit

Rock is a software framework for the development of robotic systems. The underlying component model is based on the Orocos RTT (Real Time Toolkit). Rock provides all the tools required to set up and run high-performance and reliable robotic systems for wide variety of applications in research and industry. It contains a rich collection of ready to use drivers and modules for use in your own system, and can easily be extended by adding new components.



2.5.1 Main Target Systems

- High reliability robots

2.5.2 Notable Features

- Sustainable systems with focus on error detection and reporting
- Driver support for a number sensors and actuators
- Heavily based on OROCOS toolchain

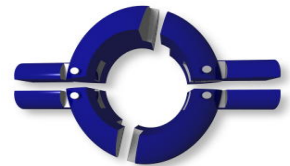


2.5.3 Related links

Reference type	Link
Documentation	https://www.rock-robotics.org/documentation/about/index.html
Support (for)	http://www.dfki.de/mailman/cgi-bin/listinfo/rock-dev
Core Repositories	https://github.com/rock-core
Package Index	https://github.com/rock-core/rock-package_set
Governance Organization	https://www.dfki.de/en/web/technologies-applications/living-labs/robotics-exploration-laboratory/
Supporting Initiatives	

2.6 Open Robot Control Software

Orocos is a portable C++ library for advanced machine and robot control. Over the years, Orocos has become a large project of middleware and tooling for development of robotics software. The main parts of this project are the Real Time Toolchain (RTT) and the Orocos Component Library (OCL).



2.7 Comparison

In order to choose the right open source robot framework and middleware many factors are important. However, for professional use cases the most important factor is long term support and availability.

Feature	ROS	ROS 2	YARP	ROCK	OROCOS
Real-time support	✗	✓	✓	✓	✓
Open source manipulation infrastructure	✓	✓	✗	✓	✗
Open source navigation infrastructure	✓	✓	✗	✗	✓
Open source perception infrastructure	✓	✓	✗	✗	✓

The table suggests that ROS2 will be the Best Practice in the near future. However, currently there are not sufficient (publicly known/available) implementations to use as a blueprint for Agriculture robotics. Therefore, at the time of writing, ROS(1) is still the Best Practice. The lack of (hard) real-time support is not a hindrance



for most agricultural applications. The remainder of this document follows our main conclusion and is therefore mostly focused on ROS(-related) best practices.



3 Best practices from a technical point of view

3.1 Common use cases in Agri-Food domain

3.1.1 Introduction

There are many robotic applications in agri-food domains. Fig 2 shows a classification of tasks as proposed by [96]. In this deliverable, we focus on the subset of the three most occurring tasks as listed by a recent survey [1]. These three are, in order of robotic complexity,

- (i) field scouting and data collection,
- (ii) weed control and targeted spraying, and
- (iii) automated harvesting robots.

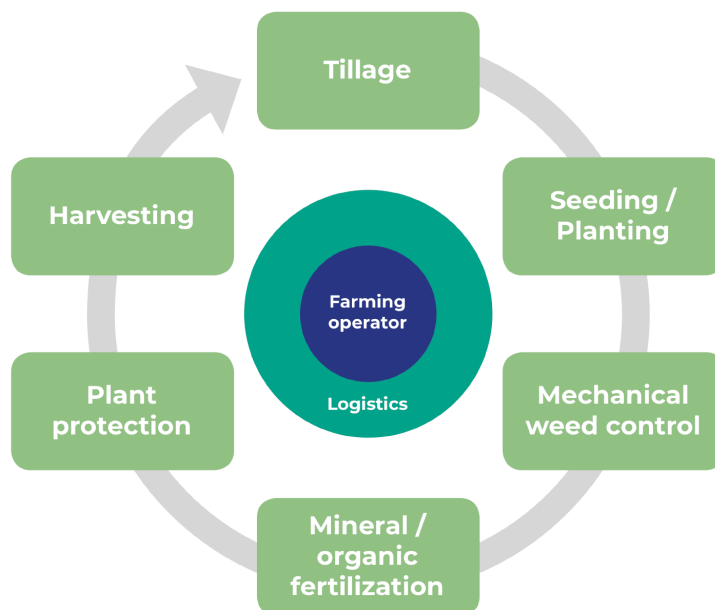


Fig 2: An overview of robot agriculture tasks, taken from [96].

3.1.2 (i) Field scouting and data collection

Table 3.1 provides an up-to-date overview of field scouting and data collection robots. Due to information availability, research projects are better represented than commercial solutions. From this overview, we select Blok's orchard robot shown in Table 3.1.a [12] as the "best practice" example due to its extensive description as well as its coverage of most common components and packages.

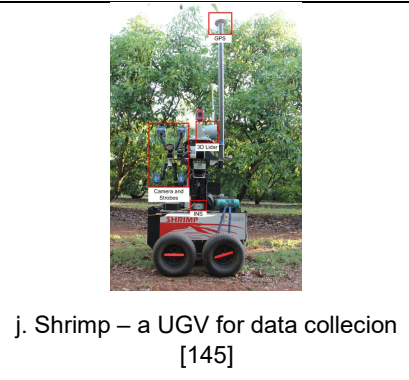
		
a. Husky A200 robot with 2D LIDAR scanner used for orchard navigation [12]	b. A prototype field survey mobile robot platform [135]	c. Husky UGV for vineyard monitoring [10, 15]
		
d. TrimBot2020 for automatic gardening [78]	e. TerraSentia for in-field plant trait data collection; Source: https://www.earthsense.co	f. Mobile Agricultural Robot Swarms (MARS) for seeding tasks [136]
		
g. VINBOT – an all-terrain mobile robot for capturing and analyzing data in a vineyard; Source: http://vinbot.eu/	h. SMP S4 – a surveillance robot to protect orchards from birds; Source: https://smprobotics.com/	i. VineRobot for monitoring vineyards; Source: http://www.vinerobot.eu/
		
j. Shrimp – a UGV for data collection [145]		

Table 3.1: An overview of field scouting and data collection robots

Besides common motion and sensing subcomponents, the specific robotic technology required for these robots is an exhaustive navigation system. Such a system comprises automatic and accurate navigation control, simultaneous localization and mapping, path planning algorithms, and three-dimensional environment

reconstructions [1]. From the detailed list of technologies in Section 3.2, the following pertain specifically to field scouting and data collection robots:

- Mobile platform
- Simulation environment
- Navigation sensors
- Internal communication
- Software framework
- SLAM (Simultaneous Localization and Mapping)
- Environment reconstruction
- Path planning

3.1.3 (ii) Weed control and targeted spraying

One of the most demanded and common applications for agricultural robots could be weed control. The following weed control and targeted spraying robot projects can be used as examples and source of inspiration. We have obtained this list mostly from various survey papers [1, 3, 53, 54].

 a. BoniRob; Source: Deepfield Robotics [32]	 b. High speed electric in-row weeding machine; Source: Tillett and Hague Technology [33]	 c. Dino – an entirely autonomous weeding robot; Source: https://www.naio-technologies.com/en/
 d. AgBot II; Source: Queensland University of Technology [142]	 e. AVO performs autonomous weeding operations; Source: https://www.ecorobotix.com/en/	 f. RIPPA – a prototype robot for shooting weeds using a micro-dose of liquid; Source: University of Sydney

 g. Tertill – a solar powered weeding robot for home gardens; Source: https://franklinrobotics.com/	 h. S55 spray robot made for automatic spraying in a greenhouse; Source: http://www.hollandgreenmachine.com	 i. SwagBot [143] – an all-terrain, four-wheeled, solar-powered robot; Source: University of Sydney
 j. Hortibot [144] – a semi-autonomous weeding robot; Source: Aarhus University	 k. Ladybird – an omni-directional robot for targeted spraying and data collection [146]	 l. Robovator – a vision based robotic hoeing machine for controlling weeds in row crops; Source: https://www.robovator.com/
 m. Odd.Bot Weed Whacker – an autonomous weed-plucking robot that uses no chemicals ; Source: https://www.odd.bot/	 n. AgroIntelli Robotti – a diesel-hydraulics autonomous tool for both for sowing and spraying; Source: http://www.agrointelli.com/index.html#home	 o. Asterix – an light-weight, autonomous farm-bot desinged for spraying herbicides on weeds only; Source: https://www.asterixproject.tech/

Table 3.2: An overview of weed control and targeted spraying robots

Weed control and targeted spraying robots are more complex than the category of field scouting and data collection robots. The additional technologies can be summarized as a targeted motion system together with a robust perception system which includes weed detection, weed and crop identification and crop localization. From the detailed technologies listed in Section 3.2, the following additional technologies pertain specifically to weed control and targeted spraying robots:

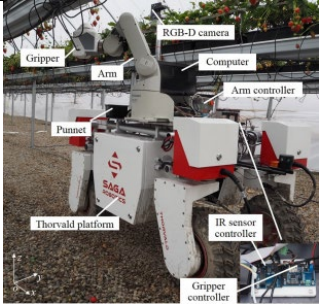
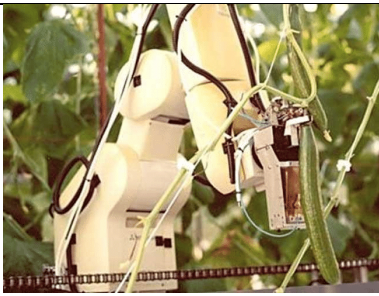
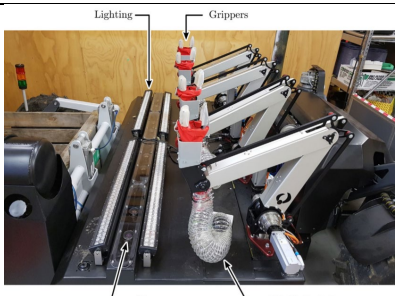
- Specific hardware components for weeding and targeted spraying
- Robot arms
- Perception hardware
- Weed/crop classification algorithms

The performance of state-of-art weed control robots is good in ideal conditions. However, in uncontrolled or semi-controlled environments, problems emerge due to the variety in lighting, density and species of weed plants, and occlusion of mixtures of plants [3]. This remains a major challenge to commercialization of weed control robots.

Although all examples in the Table 3.2 are useful sources for inspiration, at the time of writing we have selected BoniRob as the most useful example for “best practice” for weeding robotics. This choice was made based on the extensive descriptions [23, 55-58].

3.1.4 (iii) Harvesting

The third and most demanding main category of agriculture robotics is robotic harvesting. This not only requires all of the navigation capabilities of scout robots and all of the classification and positioning capabilities of weed removal robots, but adds three significant additional capabilities: crop detection, motion planning, and dexterous manipulation. The overview below shows a large number of research projects which can serve as inspiration for the development of high-performance harvesting robots.

 a. SWEEPER – a robot for harvesting sweet pepper fruit in greenhouses [147]	 b. Green Robot Cotton Harvester V 02 developed by Green Robot Machinery [139]	 c. Strawberry-harvesting robot [31]
 d. Harvey – the robotic capsicum harvester [7]	 e. Cucumber harvesting robot [148]	 f. Kiwifruit harvester mounted on the base robotic platform [149]

 g. Apple-picking robot; Source: https://www.abundantrobotics.com/	 h. Tomato harvester; Source: https://metomotion.com/	 i. Energid citrus picking system; Source: https://www.energid.com/
 j. Dual-arm tomato harvesting robot testing in the greenhouse [150]	 k. Cherry-tomato harvesting robot [151]	 l. Panasonic AI-equipped tomato harvesting robot [152]

Table 3.3: An overview of harvesting robots

Compared to weeding and targeted spraying robots, harvesting robots are more complex. The additional capabilities that set harvest robots apart from scout or weeding robots, as detailed in Section 3.2, are the following:

- Harvesting end-effectors
- Crop detection and localization
- Grasp selection
- Robot manipulator path planning

3.2 Open-source software/hardware components

3.2.1 Introduction

To avoid duplication of effort and reinventing the wheel, a great range of existing technologies from other robotics domains could be used to facilitate the transition of agricultural robotics into the field. Some technologies might need to be developed specifically for agriculture from scratch, while other technologies already developed for general robotics could be adapted to the agricultural domain, for example, autonomous vehicles, artificial intelligence and machine vision [4]. Hereby, in this section, we briefly review those technologies widely used in the agricultural domain, which are pertinent to aforementioned use cases. We also list the best practices regarding all of the specific components required for agriculture robotics. Although the focus of the document is on open-source components (which mostly entails software), we have included best practices for hardware component selection as well; not only does this provide a more complete overview of the state of the art, it also provides clarity how hardware decisions influence the use of open-source software components.

3.2.2 Hardware

Mobile platform

A common denominator in many projects is the use of a rugged, not-too-large, open-source-ready mobile platform. Examples include ClearPath's Husky robot [8] as used in projects [10,11,12,13,14,15,16] above, and Robotnik's Summit-XL [9] as used in project [17]. It is highly recommended to base at least the initial developments on such an existing, generic platform.

Hardware components specific for weeding and targeted spraying

The specific hardware for weeding and targeted spraying strongly depends on the crop and intended treatment. Although it is impossible to identify a single "best practice", one can find many inspirational examples in these papers [1,3,53,54].

Positioning hardware – robot arm

As soon as it is required to bring a spray head or mechanical weeding device to a specific position relative to the mobile base, one requires a positioning system for at least 3 degrees of freedom. Two best practices have been identified. First, for fast and lightweight motions with limited reach, a parallel robot construction is often used and the most popular type is "Delta robot" [59, 60]. Commercially available parallel robots are developed for static systems, so the best practice is that the hardware is developed specifically for the intended application, while the control software is taken from a common source (either commercial [61, 62] or open-source [63, 64]). Second, for motions which require larger reach and full orientation control, at the cost of operational speed, it is common to use a commercial serial robot manipulator arm. Due to the mobile weight and power limitations, the best practice is to use a lightweight industrial arm such as a Fanuc LR Mate [65], a Universal Robot [66], a Franka Emika Panda [67] or an even more lightweight wheel-chair specific robot arm [68]. Available ROS drivers make it fairly straightforward to integrate these robot arms into the mobile robot.

End-effector for harvesting

From a thorough review of all available literature on harvesting robots, it is clear that the end effector will always be a very crop-specific and process-specific design. Each project has a unique gripper or cutter or other type of harvesting end-effector. The best practice here appears to be to take inspiration from all available publications, specifically those fully dedicated to designing (harvesting) end-effector [27, 31, 74, 78-82], and then to aim for a fast multi-prototype design process to handle unforeseen interactions with the crop [83, 84]. The end-effector must usually be moved in 6 dimensions for proper harvesting, and so we reiterate our previous best practice recommendation of using a standard and lightweight serial robot arm as commonly used in other industries. Efforts to make own robot arm designs to optimize for lower cost and higher speed (e.g. attempting to trade those off for lower required accuracy) usually don't succeed due to underestimation of the design efforts necessary for creating robust hardware and software.

3.2.3 Sensors

In robotics, sensors could be categorised into two groups: internal and external. Internal sensors are used to measure robot parameters relative to the reference frame of the robot, such as a joint angle, a linkage deflection, or a gripping force. External sensors are used to measure the environment and the position of the robot relative to that environment [137]. The sensors that are most widely used in robotics and supported by official ROS packages [121] can be summarized as follows:



- Inertial sensors (IMU)
- Orientation sensors (GPS)
- Laser range sensors (1D range finders, 2D range finders)
- 3D sensors (range finders & RGB-D cameras)

Navigation sensors

For outdoor navigation, a common best practice is the use of GNSS [125], typically Differential GPS for higher accuracy or RTK-GPS for extremely high accuracy [23]. Some research is done on purely vision-based navigation [24, 25] in order to prevent the perceived high cost for GPS, but this is not considered a best practice. For indoor (greenhouse) navigation, where GPS does not work well, there is no best practice yet that is commonly shared, and novel ideas such as Artificial Potential Fields are explored [26].

Additionally, field robots commonly use a LiDAR sensor [23, 27] to obtain a 3D scan of its near surroundings and an IMU sensor for orientation. There are many parallels with autonomous vehicle projects here, and many opportunities to reuse both research and available solutions.

Crop/weed perception sensors

Best practices include 2D and 3D image sensors and multi-spectral sensors [69-72]. In almost all systems, the developers have chosen to shield sunlight as much as possible, as this dramatically interferes with the sensors. A typical construction is that of a black, shielded casing around the sensors, which is being held as closely above the ground as possible [55, 73].

3.2.4 Low-level communication protocol

Internal communication

Since CAN-bus has been adopted as ISO standard 11783 (also known as “ISOBUS”[34, 35]) for agriculture machinery, a best practice is to use this for the low-level communication between motion controllers, actuators, and other components. Unfortunately, this conflicts with the internal low-level communication inside common mobile research platforms such as the ClearPath’s Husky as mentioned above. A best practice is to ensure the availability of ISOBUS-compatible communication for easy extension of the system with additional components. This is, however, limited to low-level communication only. For higher-level communication, a best practice is to adhere to the communication standards of a software framework as described below.

3.2.5 Overall software framework

ROS: overall software framework

One of the strongest common denominators of all field scouting and data collection robots is the use of ROS (Robot Operating System) as the software framework. Although there are many other frameworks as well [128, 129], ROS has become the de-facto standard. Besides an overwhelming amount of generic examples and tutorials to use ROS for mobile robots [36-39], there are a number of excellent descriptions of the specifics of ROS in agricultural settings [28, 40-42]. Best practices are collected and demonstrated in the open-source projects FroboMind [5, 43], AgROS [20], and ROS-Agriculture [29, 30]. The software framework allows an almost unlimited extension of the robot’s capabilities through adding more and more (open-source) software packages written for this framework. For the current category of robots, which basically only need to navigate,

the best practice includes packages for SLAM, path planning and environment reconstruction as elaborated below.

3.2.6 Navigation algorithm

SLAM algorithm

SLAM stands for Simultaneous Localization and Mapping, which is a category of algorithms that has various implementations [44-46, 130]. All mobile robotic devices including (semi-) self-driving cars use this type of algorithm. For the current version of this document, it is unclear if there already is a best practice regarding the choice and implementation of SLAM for agriculture robotics. The natural yet repetitive environment makes it hard to use landmarks for map-building and navigation, yet (at least for outdoor agriculture) the GNSS is highly accurate.

Environment reconstruction

Best practice examples of agricultural robots typically use a LiDAR as illustrated above, which provides 3D information. The most common way for initial storage of that data is as a “Point Cloud”. A collection of effective algorithms to process this kind of data is available through the open-source Point Cloud Library [47]. Good examples for the application of this library in agricultural robotics can be found in [48-51].

Path planning algorithm

Path planning is the final type of generic algorithm that will be present in all mobile robots [52]. In agriculture, path planning is in some regards simpler than in challenging environments such as crowded public spaces. A difficult challenge remains the presence of foliage which should not be considered as a hard constraint, but can (and must) occasionally be pushed aside. Good examples of path planning in agriculture settings can be found in [10, 15, 27, 130].

ROS navigation stack

It's essential for an autonomous robot to navigate itself across a crop field without human assistance, e.g. field scouting robots for data collection. Generally speaking, an exhaustive navigation system is required a combination of three fundamental competences, that is, mapping, localization, and path planning [6]. There are many software toolboxes/packages capable of providing those competences. To the best of our knowledge, one of the most well-known software packages used in robotics is the *Navigation Stack* in ROS 1. Inputs generally required in Navigation Stack are odometry and sensor data such as a continuous stream of 2D/3D scans or 3D point clouds of the immediate environment. Outputs are velocity commands sent to a mobile base.

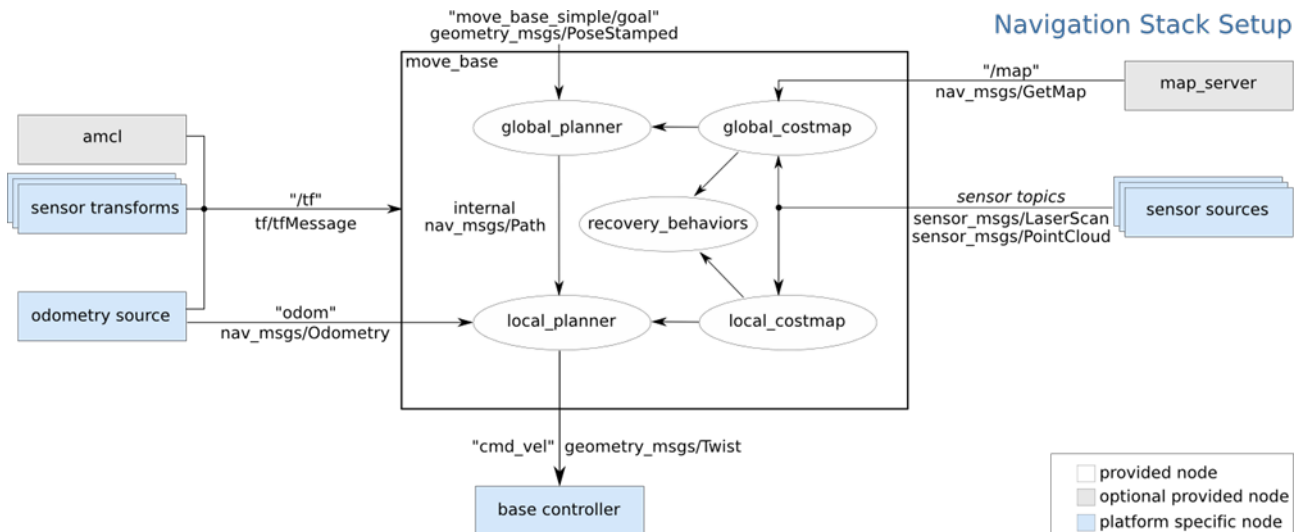


Fig 3: Overview of Navigation Stack in ROS 1

There is Navigation Stack in ROS 2 [138] as well. The main changes from ROS 2 is that the move_base (nav2_simple_navigator) has been split into multiple components (nav2_navfn_planner and nav2_dwb_controller) and a behaviour tree is implemented to orchestrate these components. These changes provide flexibility and extensibility of the navigation stack behaviour as it is possible to replace any of these nodes at launch/run time.

3.2.7 Crop/weed sensing algorithms

Weed / crop classification algorithms

The choice for perception sensors is linked to the choice for classification algorithms. Currently, the best practice is to use Deep Learning algorithms. Within the span of just a few years, this approach has completely taken over from more “old-fashioned” classification algorithms which are still in use [73-75]. A few years ago, the best practice would probably consist of a combination of color segmentation and Bayes classification or Support Vector Machines, where the algorithm’s parameter settings would be optimized with training data, which would need to be re-trained for each season.

Deep Learning is a generic term, and for agriculture applications many variations are in use [76]. Obtaining and properly labeling the training sensor data is crucial for success, [76] provides a list of available open datasets

Crop detection and localization

Compared to weeding, harvesting leads to much more complex tasks of detection, classification, and localization. Crops are often partially occluded [85], and misinterpretation of the cutting location of the crop might result in cutting vital parts of the plant and/or damaging the crop [86]. This is still an active field of research, and the best practice appears to be to aim for a combination of detection methods [87-89].

3.2.8 Simulation

Simulation

An essential aspect for effective robot development is the ability to test to high fidelity in simulation environments. [18] provides an excellent survey of simulation tools that allow initial development with little overhead cost. The survey *“concluded that V-REP <now CoppeliaSim> offers a higher number of useful features, such as multiple physics engine, comprehensive robot model library, and the ability of a user to interact with the world during simulation and, most importantly, mesh manipulation and optimization, however it is the most CPU resource-hungry of the simulators.”* Another favorite is the ROS-native Gazebo simulation environment which is used abundantly in (agriculture) robotics projects. In addition to the environments further listed in [18], we also encountered a specifically developed agriculture framework [19], an agriculture emulation framework AgROS [20], the possibility to use Unreal Engine [21] or the content-rich and popular “Farming Simulator” game environment [22]. For further testing towards successful real-world implementations, we see an increasing drive towards “hardware-in-the-loop” or “human-in-the-loop” simulations, where parts of the system are simulated and other parts are real [126, 127].

3.2.9 Manipulation

Grasp selection

Once the location and orientation of the crop has been determined, the robot must decide how to position the end effector. This is a constrained optimization problem where the stem should be cut but no other plant parts should be damaged. Within the field of generic robotics, a best practice we believe is to do grasp selection with a Deep Learning algorithm as well [90-94], Calculation time used to be a challenge, but very fast algorithms are becoming available [95].

Manipulator: path planning

While weeding end-effectors can usually move in a straight line toward the weed, for crop harvesting there are often severe obstacles such as branches [77, 141] and other unripe or un(der)developed crops. This requires advanced path planning algorithms to avoid those obstacles. The current best practice is to use a randomized or optimizing motion planner as implemented in OMPL which can be used through the package MoveIt in ROS. New motion planning algorithms are still in development, and a very interesting research avenue is to plan motions that purposefully push parts of the obstacles away [31]. Retrieving the crop is yet another challenging motion planning problem, because now a collision-free motion for the manipulator *including the crop* must be found. A best practice example can be found in [96].

ROS MoveIt

MoveIt [132] is a user-friendly open-source robotics manipulation platform which runs on top of ROS. It leverages ROS software by providing high-level functionalities for robotics manipulation such as collision checking, inverse kinematic algorithms, trajectory processing, etc. To the best of our knowledge, it is one of the most widely used open-source robotics manipulation platforms for developing commercial applications, prototyping designs, and benchmarking algorithms. It has been recommended and used for agricultural robots especially on harvesting robots [7, 28, 41].

4 Best practices from an organizational point of view

In this chapter, we provide an overview of the *non-technical* best practices to start working on agricultural robotics. The previous chapter listed all of the technical details to create a successful agricultural robot, but how should one get started from an organizational point of view? The suggestions in this chapter are useful for anyone in the agriculture value chain, and are probably most relevant for those interested in the actual development of robot systems.

4.1 Sources of inspiration

When starting from scratch or re-engaging in agriculture robotic development, it is good practice to be 'connected' with simultaneous developments and to have access to up-to-date information and involved communities. A good place to start are the high-quality review documents and other overviews that have been produced. We recommend the following sources as point of departure:

- "Scouting the Autonomous Agricultural Machinery Market". [96] This report identifies relevant factors that will influence the development, estimate their importance, understand the biggest uncertainties, and get a feeling of the state of the practice and the state of the art, as well as on how the experts see future developments. Elements of this report will appear in other paragraphs below.
- Multi-Annual Roadmap for Robotics. [97] This document was assembled with the help of a European-wide network of robotics experts and contains a timeline for technological developments. There is a full chapter dedicated to agriculture robotics.
- "Research and development in agricultural robotics: A perspective of digital farming." [1] This paper was used as one of the main sources for the overviews in Chapter 2. It contains inspiring examples and many useful references.

An additional best practice is to get 'connected' by participating in symposia and conferences. A number of such events cater exactly to the needs for agriculture roboticists:

- FIRA [98], every year in December in France.
- ROScon [99], fully focused on ROS.
- International Conference on Agricultural Robotics, Automation and Control [100]

Finally, the best way to stay connected and informed is to be(come) involved in the key online communities where open-source software and best practices are exchanged:

- ROS-Agriculture [101]
- FroboMind [43]
- IEEE Agricultural Robotics and Automation Technical Committee [102]

4.2 Open-source software/platforms/framework

There are a number of widely used open-source software platforms that deserve a more extensive description. We will briefly summarize the usefulness of these platforms for agriculture robotic applications, provide pointers to the organizational structure of these platforms, and illustrate the best practices to make use of these platforms.

4.2.1 ROS

The Robot Operating System (ROS) is an open-source, meta-operating system for writing robot software. It provides OS-like features such as hardware abstraction, low-level device control, implementation of commonly used functionality, message-passing between processes, and package management. It also provides a collection of tools, libraries, and conventions for performing different complex and robust robotic tasks across multiple computers/robotics platforms. ROS has become a de facto standard for robot application development.

From the start, ROS was developed and overseen mainly by Willow Garage. From 2013 till now, the primary development of ROS has been taken over by Open Robotics. Over the years, many other organizations/institutions have also made contributions to ROS development as it's an open-source project/framework. The worldwide approval and use of ROS can be attributed to the power and wisdom of the crowd. However, the governance framework in ROS community was not clearly identified earlier on. Therefore, starting from ROS2, in order to broaden participation to accelerate ROS 2 delivery, a Technical Steering Committee (TSC) has been established. TSC is responsible for effective planning, decision making and supervision for the technical direction that the project takes, i.e. determining the project roadmap, developing core tools and libraries, and establishing working groups to focus on important topics.

With regard to management and dissemination, ROS has a “ROS Discourse” which is a place to talk about ROS and ROS related things. There is also a site called “ROS Answers” which is dedicated to answering questions of the ROS community. In addition to these online forums, the following conferences and community meetups are also highly relevant:

- **ROSCon**
ROSCon is a developers conference, in the model of PyCon and BoostCon. It has occurred every year since 2012 for ROS developers of all levels, beginner to expert, to spend two days learning from and networking with the ROS community. It is a must-attend event to meet world developers and keep abreast of ROS community. There are also national editions of ROSCon such as ROSCon Japan, ROSCon France, and ROSCon Hong Kong.
- **ROS-Industrial Conference**
- **ROS-Industrial Training**
- **ROS-A Community Meeting**

4.2.2 OpenCV, PCL

In addition to ROS as the main robotics framework in use in the best practices of today, a number of other open-source frameworks are in use. For image processing, most often one relies on OpenCV [102-106]. Modern machine learning approaches such as Deep Learning (next paragraph) do not replace OpenCV but work in harmony with it. Another key framework is the Point Cloud Library (PCL) [47-51] which contains algorithms for processing 3D image data.

4.2.3 MRPT, OMPL, MoveIt, OpenRave

For motion planning, path planning, and grasp planning, there are a number of open-source projects available which are all linked well with ROS and which are being widely used in all robotics applications, such as MRPT for navigation [130], OMPL for robot arm motion planning [131], MoveIt [132] as a wrapper of that for ROS, and OpenRave [133] which is often used for grasp planning.

4.2.4 Deep Learning frameworks and datasets

Recently, Deep Learning took the field of robotics by storm, outperforming all other tools for image (or other data) classification. Although some state of the art agricultural robotic systems do not yet make use of Deep Learning (e.g. [73, 75]), we expect that this will change very quickly. The use of Deep Learning algorithms is clearly considered as a best practice for agriculture robotics [53, 76]. It has already been deployed successfully for various agriculture tasks [55, 56, 78, 110-112].

The robot developer currently has a choice between various Deep Learning frameworks such as Google Tensorflow [107], Caffe [108], or PyTorch [109] and some more. An overview of 40 agriculture robotics projects [76] shows that there is not yet a clear preference for any one of those frameworks.

Deep Learning algorithms are useful only if there is sufficient high-quality data available for training. From an organizational point of view, the best practice is to search for a proven combination of (1) a Deep Learning framework, and (2) an available dataset relevant for the specific application. A point of departure for re-using or creating agriculture-specific datasets is to first assess the most-used presently available datasets, as shown in Fig 4.

Fig 4: A list of publicly-available datasets related to agriculture [76]

No.	Organization/Dataset	Description of dataset	Source
1.	Image-Net Dataset	Images of various plants (trees, vegetables, flowers)	http://image-net.org/explore?wnid=n07707451
2.	ImageNet Large Scale Visual Recognition Challenge (ILSVRC)	Images that allow object localization and detection	http://image-net.org/challenges/LSVRC/2017/#det
3.	University of Arkansas, Plants Dataset	Herbicide injury image database	https://plants.uaex.edu/herbicide/ http://www.uaex.edu/yard-garden/resource-library/diseases/
4.	EPFL, Plant Village Dataset	Images of various crops and their diseases	https://www.plantvillage.org/en/crops
5.	Leafsnap Dataset	Leaves from 185 tree species from the Northeastern United States.	http://leafsnap.com/dataset/
6.	LifeCLEF Dataset	Identity, geographic distribution and uses of plants	http://www.imageclef.org/2014/lifeclef/plant
7.	PASCAL Visual Object Classes Dataset	Images of various animals (birds, cats, cows, dogs, horses, sheep etc.)	http://host.robots.ox.ac.uk/pascal/VOC/
8.	Africa Soil Information Service (AFSIS) dataset	Continent-wide digital soil maps for sub-Saharan Africa	http://africasoils.net/services/data/
9.	UC Merced Land Use Dataset	A 21 class land use image dataset	http://vision.ucmerced.edu/datasets/landuse.html
10.	MalayaKew Dataset	Scan-like images of leaves from 44 species classes.	http://web.fsktm.um.edu.my/~cschan/downloads_MKLeaf_dataset.html
11.	Crop/Weed Field Image Dataset	Field images, vegetation segmentation masks and crop/weed plant type annotations.	https://github.com/cwfid/dataset https://pdfs.semanticscholar.org/58a0/9b1351ddb447e6abdede7233a4794d538155.pdf
12.	University of Bonn	Sugar beets dataset for plant classification as well as Photogrammetry, IGG, localization and mapping.	http://www.ipb.uni-bonn.de/data/
13.	Flavia leaf dataset	Leaf images of 32 plants.	http://flavia.sourceforge.net/
14.	Syngenta Crop Challenge 2017	2,267 of corn hybrids in 2,122 of locations between 2008 and 2016, together with weather and soil conditions	https://www.ideaconnection.com/syngenta-crop-challenge/challenge.php

4.2.5 Best practice regarding open-source software licensing

As we have shown in the previous sections, the best practice examples typically include multiple (Free) Open Source Software (FOSS) packages. Although the internet has been running for decades on (F)OSS, with Linux being the primary example, only recently robotics companies have started to embrace (F)OSS. The fast access to state-of-the-art algorithms and collaborative (hence cheaper) developments outweigh the common not-invented-here attitude. Making use of (F)OSS for commercial robotic systems requires proper assessment of the software licences, for which we have collected the best practices. A first yet quite complete overview on licensing issues can be found on dedicated websites [113-115]

Importantly, a common misunderstanding about the “business friendliness” of open-source software licenses must be corrected [116]. Although *some* licenses, such as (L)GPL [140] live up to their difficult reputation that any new software also must be released as FOSS, this is not true for most licenses that are used for the recommended frameworks such as ROS. Most often, ROS packages are released under Apache 2.0, BSD, or MIT licenses [113] which *allow use of the free open-source software inside closed commercial software products*.

The recommended best practice before commencing agriculture robot product development is to conduct a thorough licensing trace to ensure that there are no hidden liabilities. Note that software packages *without* a license are more of a liability than those with a license, because the authors formally still have all the rights, even if they make their source code publicly available.

4.3 Standards

From [96] we copy the most well-known standards for agricultural robotics. Adhering to these standards and contributing to their development is considered as best (future-proof) practice.

The most well-known standardization efforts are the following:

- Machine-to-Machine Communications: The communications standard ISOBUS (ISO standard 11783) [35] is for standardizing farm equipment that creates and handles farm data. The ISO standard 11783 defines serial control and communications data networks for tractors and agricultural machinery. In order to achieve a large degree of autonomy, data produced by agricultural vehicles must be processed and reasoning needs to be performed. Such data might first be sent to the cloud infrastructure of the respective manufacturer before it is then shared between different clouds through standardized interfaces, semantics and data structures.
- SAE J3016: Taxonomy and Definitions for Terms Related to Automate Driving [117] defines terminology around automated driving such as automation levels.
- UL4600 – Standard for Safety for The Evaluation of Autonomous Products [118] provides a set of normative requirements on how to build a proper safety case for autonomous systems. The scope of this standard is mostly on autonomous driving with a focus on what things need to be assured. The standard is scheduled to be released in 2020.
- SOTIF – Safety of the Intended Functionality [119] deals with assuring the absence of unreasonable risk due to hazards resulting from functional insufficiencies of the intended functionality or from reasonably foreseeable misuse by persons. Practically, this refers to creating sufficient situational awareness and is targeted at finding problems induced by the incapability of sensors and sensor fusion to properly determine relevant properties of the environment. SOTIF is a very important standard for complex decision logic relying on complex situational awareness. As of its 2019 release, it deals only with automation levels L1 and L2 (according to SAE J3016 automation scale) explicitly,

but the working group is currently extending the standard up to level 5 (highest level of driving automation).

4.4 Legal issues

Sources such as [96] indicate that currently, there is no comprehensive legal framework for the use of (semi/full) autonomous robots in agriculture. Safety, liability, privacy, and data management issues still need to be resolved. This document does not serve to solve these issues. Instead, we provide an overview of how the best practice examples in industry currently operate with agriculture robotics, given the current legal vacuum. We recommend for future research projects to focus on the legal aspects pertaining to the following issues in agriculture robots:

- Maintaining human supervision
- Human robot collaboration (master-slave trucks)
- Confining the operational spaces for the robots
- Analyzing whether there are already agreements with insurance companies?
- Analyzing the tendency to outsource liability to the supplier?

4.5 Social aspects

Legal issues are not the only non-technical considerations that may hamper the widespread adoption of agriculture robotics. Devitt [120] analysed the social aspects that influence initial adoption and sustained use of robotics in agricultural enterprises. Although we are looking for best practices, the paper by Devitt provides the opposite; the cognitive factors that may lead to the lack of adoption of robotic and autonomous systems in agriculture. The main reasons for not adopting driverless tractors, agricultural crop picking robots, and UAV's are: i) inability to generate trust; ii) loss of farming knowledge; and iii) reduced social cognition. Although no concrete best practices are provided, we conclude that implementation success is highest if the robotic system performs a limited, well defined task, where all robot decisions are easy to interpret, and with a clear economic benefit.

5 Conclusion and Future work

5.1 Guide to replication

Reproducibility is key for useful Best Practices. The literature references in Chapter 6 and the list of datasets in Figure 4 already provide an entrance for newcomers to the field. Typically, the precise environmental circumstances and precise hardware setup do not allow exact reproduction of the presented research results, and typically the authors need to preserve some confidentiality regarding the business details. Therefore, the best approach to reproduction is by following the very open and accessible ROS tutorials and information. For Agriculture applications specifically, some community contributors have created a set of recommendations and links to further detailed information. Readers who intend to reproduce agriculture robot results are strongly recommended to follow these suggestions. For completeness, we provide a verbatim copy here of the information found at <http://wiki.ros.org/agriculture> (accessed at 11-11-2021). Rather than following the text below (which might become outdated), we urge the reader to go to the original online resource.

5.1.1 ROS

- You can download a prebuilt image for a raspberry pi or virtual machine here: Ubiquity Robotics [Download](#)
- If you would like to install ROS on your Ubuntu machine we use the install script from Linorobot. [Download](#)
- [Move Base Flex Wiki](#) Move Base Flex (MBF) is a backwards-compatible replacement for move_base. MBF can use existing plugins for move_base, and provides an enhanced version of the planner, controller and recovery plugin ROS interfaces.

5.1.2 Packages

- [Linorobot](#) Linorobot supports different robot bases you can build from the ground up. Supports: 2WD, 4WD, Mecanum Drive, and Ackermann Steering.
- [Greenzie Area Planner](#) Boustrophedon Planner is a coverage path planner that implements a modified cellular decomposition algorithm.
- [Nobleo Area Coverage](#) Full Coverage Path Planner (FCPP) Full coverage path planning provides a move_base_flex plugin that can plan a path that will fully cover a given area

5.1.3 Image Datasets

VineSet - A Large Vine Trunk Image Collection and Annotation using the Pascal VOC format. Nuno Namora Monteiro, André Silva Aguiar, Filipe Neves dos Santos, and Armando Jorge Sousa: Laboratory of Robotics and IoT for Smart Precision Agriculture and Forestry at CRIIS (Centre for Robotics in Industry and Intelligent Systems). [Download Vine Dataset](#)

Embrapa Wine Grape Instance Segmentation Dataset - Embrapa WGISD <https://github.com/thasant/wgisd>

Sebastian Haug, Jörn Ostermann: A Crop/Weed Field Image Dataset for the Evaluation of Computer Vision Based Precision Agriculture Tasks, CVPPP 2014 Workshop, ECCV 2014" You can download the complete crop/weed field image dataset here: [Download CWFID](#)

Datasets listed in this paper by Andreas Kamilaris and Francesc X. Prenafeta-Boldú Institute for Food and Agricultural Research and Technology (IRTA)

Deep Learning in Agriculture: A Survey <https://arxiv.org/pdf/1807.11809.pdf>



- Image-Net Dataset - Images of various plants (trees, vegetables, flowers)
Download - <http://image-net.org/explore?wnid=n07707451>
- ImageNet Large Scale - Visual Recognition Challenge (ILSVRC) - Images that allow object localization and detection
Download - <http://image-net.org/challenges/LSVRC/2017/#det>
- University of Arkansas, Plants Dataset - Herbicide injury image database
Download - <https://plants.uaex.edu/herbicide/>
Download - <http://www.uaex.edu/yard-garden/resource-library/diseases/>
- EPFL, Plant Village Dataset - Images of various crops and their diseases
Download - <https://www.plantvillage.org/en/crops>
- Leafsnap Dataset - Leaves from 185 tree species from the Northeastern United States.
Download - <http://leafsnap.com/dataset/>
- LifeCLEF Dataset - Identity, geographic distribution and uses of plants
Download - <http://www.imageclef.org/2014/lifeclef/plant>
- PASCAL Visual Object Classes Dataset - Images of various animals (birds, cats, cows, dogs, horses, sheep etc.)
Download - <http://host.robots.ox.ac.uk/pascal/VOC/>
- Africa Soil Information Service (AFSIS) dataset, Continent-wide digital soil maps for sub-Saharan Africa
Download - <http://africasoils.net/services/data/>
- UC Merced Land Use Dataset - A 21 class land use image dataset
Download - <http://vision.ucmerced.edu/datasets/landuse.html>
- MalayaKew Dataset - Scan-like images of leaves from 44 species classes.
Download - http://web.fsktm.um.edu.my/~cschan/downloads_MKLeaf_dataset.html
- Crop/Weed Field Image Dataset - Field images, vegetation segmentation masks and crop/weed plant type annotations.
Download - <https://github.com/cwfid/dataset>
Download - <https://pdfs.semanticscholar.org/58a0/9b1351ddb447e6abdede7233a4794d538155.pdf>
- University of Bonn Photogrammetry, IGG - Sugar beets dataset for plant classification as well as localization and mapping.
Download - <http://www.ipb.uni-bonn.de/data/>
- Flavia leaf dataset - Leaf images of 32 plants.
Download - <http://flavia.sourceforge.net/>
- Syngenta Crop Challenge 2017 - 2,267 of corn hybrids in 2,122 of locations between 2008 and 2016, together with weather and soil conditions
Download - <https://www.ideaconnection.com/syngenta-cropchallenge/challenge.php>

5.1.4 Resources

Resources and information about navigation algorithms. Robotic path planning in the field of agriculture is largely focused on area coverage. Here are some research papers on the topic that try to solve the problem:

- [Coverage Path Planning: The Boustrophedon Decomposition](<https://www.ri.cmu.edu/publications/coverage-path-planning-the-boustrophedon-decomposition/>) - Howie Choset, Philippe Pignon
- [Morse Decompositions for Coverage Tasks](<http://biorobotics.ri.cmu.edu/papers/paperUploads/A028807.pdf>) - Ercan U. Acar, Howie Choset, Alfred A. Rizzi, Prasad N. Atkar, Douglas Hull
- [Optimal Field Coverage Path Planning on 2D and 3D Surfaces](<https://lib.dr.iastate.edu/cgi/viewcontent.cgi?httpsredir=1&article=3239&context=etd>) - Jian Jin, Iowa State University



- [Complete Coverage Path Planning in an Agricultural Environment](<https://lib.dr.iastate.edu/cgi/viewcontent.cgi?httpsredir=1&article=3053&context=etd>) - Theresa Marie Driscoll, Iowa State University

Other resources on coverage path planning:

- [Coverage and Search Algorithms](<http://www2.cs.siu.edu/~hexmoor/classes/CS404-S09/Coverage.pdf>) - Southern Illinois University
- [A Survey on Coverage Path Planning for Robotics](http://robots.engin.umich.edu/~egalcera/papers/galceran_ras2013.pdf) - Enric Galceran and Marc Carreras, University of Girona
- [On Complete Coverage Path Planning Algorithms for Non-holonomic Mobile Robots: Survey and Challenges](<https://pdfs.semanticscholar.org/ee6b/dd20dd58de3c4fe646103e76b46237821d38.pdf>) - Amna Khan, Iram Noreen, Zulfiqar Habib - Department of Computer Science, COMSATS Institute of Information Technology, Lahore

Path following

- [Pure Pursuit](<https://github.com/FRC3184/purepursuit>)
- [Robot Mower 2D Navigation](https://github.com/inuex3/robot_mower_2dnav)
- [simple coverage path planner ROS](<https://youtu.be/8A9DcxI0EAU>)

Visual Navigation

* [Visual Teach & Repeat Overview](<https://youtu.be/GAveEaNZZZE>)

5.1.5 Hardware

- [ROS 3D Camera's](#) 3D camera survey from ROS Industrial
- [Waterproof Ultrasonic](#) Ultrasonic Distance Measuring
- [Table of hardware](#) List of hardware reviewed.

5.2 Conclusion

The purpose of this document is to provide an overview of the state of the art of agriculture robotics, with a focus on open-source best practices. The overall conclusion is that the best practice, as a basis for future open agriculture robots, contains the following elements (not all are needed, depending on the exact application):

- A commercial, open-source ready mobile platform
- A commercial delta-robot or 6-DoF serial manipulator
- A custom application-specific end-effector
- Low-level communication adherence to ISO standard 11783 (ISOBUS)
- ROS as the main software framework, OpenCV and PCL as additional frameworks
- A combination of GNSS, IMU, LiDAR, and RGB-D sensors
- SLAM and path planning algorithms for navigation
- Deep Learning for crop/weed classification
- Manipulator motion and grasp planning algorithms

The references section contains more than 100 literature sources with details about each of these elements.



5.3 Future work: ROS-Agriculture Europe

One of the identified topics for future work regarding the establishment of frameworks for software sharing and re-use would be to further apply the initial best practices more comprehensively in ROS-Agriculture Europe. Covering a great deal of wide-ranging information in agriculture robotics, we believe this deliverable should constitute clear objectives and guidelines for ROS-Agriculture Europe. The current ROS-Agriculture Europe Community has already been built and established on a small scale in line with the aforementioned element in the conclusion section, i.e. ROS as the main software framework.

We have monthly community meetings since January, 2020. Up till now, on the technical side, what has been started and set up in ROS-A Europe are the dataset working group, the simulation working group, and some initial pilot projects.

Dataset working group:

One of primary objectives of this working group is to establish an agricultural-specific common/standard annotation for datasets. We have broken down this goal into several actionable steps, i.e. (1) create a centralized index of all the available agriculture datasets (2) list the format of the annotations and annotation tools which have been used and (3) gather a collection of relevant publications [123].

As mentioned in Section 3.2.3, “deep learning algorithms are useful only if there is sufficient high-quality data available for training”, however, collecting real data is tedious and time-consuming. This leads to the creation of another working group: the Simulation working group.

Simulation working group:

The main advantage of using simulation is to accelerate development of intellectual property. If the simulation is fairly photo-realistic, we could transfer simulated images to real-world images or reduce the simulation-to-reality gap. Synthetic datasets could play an important role for testing machine learning algorithms. Therefore, we have realized the necessity of having a simulation setup which is representative for real world agriculture. One of our small pilot projects, as a proof of concept, is to use FarmSim19 [22] to tele-operate a vehicle using ROS.

On the other hand, in terms of the establishment of governance framework, ROS-A Europe is still in the conception and initiation phase. At the current stage, we agree that clear governance structure/consortium should be a natural progression rather than an objective imposed forcibly. However, it is always nice to envision the future and keep long-term goals in mind, so we have touched upon the pros and cons of having a consortium based on the ROS-Industrial experience in several meetings. Based on the experience from other partners, we consider the Zephyr project [134] as the best practice for governance structure. Although the Zephyr project is not pertinent to agricultural robotics, the governance framework is a mechanism for management applied in any organizations/communities.

Zephyr project

The following texts were mostly taken from [134]:

“Zephyr was initially developed by Wind River Systems but has become a project of the Linux Foundation. The project is composed of two governing groups: administrative and technical. The



administrative leaders meet in a Governing Board that approves the direction and initiatives for the project. The technical leadership consists of subsystem maintainers. The Technical Steering Committee (TSC) functions as a bridge between these groups. The TSC appoints a chair who represents the interests of the TSC on the Governing Board and also works with the TSC to find solutions per the direction of Governing Board.

The governing board chooses policies, articulates strategy and provides guidance to the technical steering committee. The technical steering committee serves as highest technical decision body consisting of project maintainers. It sets the technical direction for the project and coordinates cross-community collaboration. Each member organization provides an administrative representative to the project's Governing Board, and a technical representative to the Technical Steering Committee.

In choosing maintainers from the community of project developers, the TSC evaluates the needs of the project as a whole and the subsystem or component, taking into account the active participation of the individual. This results in a system of governance that relies on merit and trust as well as participation and transparency.”

Even though we are currently at an early-stage of development, we strongly believe that, given the reinforcement by this deliverable, we will be able to coordinate with other partners and provide an open software platform with much higher level of reusability and robustness for the Agri-food robotics.



6 References

- [1] Shamshiri R R, Weltzien C, Hameed I A, Yule I J, Griff T E, Balasundram S K, et al. Research and development in agricultural robotics: A perspective of digital farming. *Int J Agric & Biol Eng*, 2018; 11(4): 1–14.
- [2] Premebida, Cristiano & Ambrus, Rares & Marton, Zoltan. (2018). Intelligent Robotic Perception Systems. 10.5772/intechopen.79742.
- [3] Steward, B.L., Gai, J., & Tang, L. (2019). The use of agricultural robots in weed management and control.
- [4] Duckett T, Pearson S, Blackmore S, Grieve B, Wilson P, Gill H et al. *Agricultural Robotics: The Future of Robotic Agriculture*. London: UK-RAS Network, 2018. 36 p. (UK-RAS White Papers).
- [5] Jensen, Kjeld & Larsen, Morten & Nielsen, Søren & Larsen, Leon & Olsen, Kent & Jørgensen, Rasmus. (2014). Towards an Open Software Platform for Field Robots in Precision Agriculture. *Robotics*. 3. 207-234. 10.3390/robotics3020207.
- [6] Nurmaini, S., & Tutuko, B. (2017). Intelligent Robotics Navigation System: Problems, Methods, and Algorithm. *International Journal of Electrical and Computer Engineering*, 7, 3711-3726.
- [7] C. Lehnert, A. English, C. McCool, A. W. Tow and T. Perez, "Autonomous Sweet Pepper Harvesting for Protected Cropping Systems," in *IEEE Robotics and Automation Letters*, vol. 2, no. 2, pp. 872-879, April 2017, doi: 10.1109/LRA.2017.2655622.
- [8] <https://clearpathrobotics.com/>
- [9] <https://www.robotnik.eu/>
- [10] <http://www.grape-project.eu/>
- [11] <https://news.ucmerced.edu/news/2016/robots-and-people-working-together-save-water-and-enhance-agriculture>
- [12] Blok, Pieter M. ; van Boheemen, Koen ; van Evert, Frits K. ; IJsselmuiden, Joris ; Kim, Gook Hwan. / Robot navigation in orchards with localization based on Particle filter and Kalman filter. In: *Computers and Electronics in Agriculture*. 2019 ; Vol. 157. pp. 261-269.
- [13] Gan, H.; Lee,W.S. Development of a navigation system for a smart farm. *IFAC-PapersOnLine* 2018, 51, 1–4. [[CrossRef](#)]
- [14] Reina, G.; Milella, A.; Galati, R. Terrain assessment for precision agriculture using vehicle dynamic modelling. *Biosyst. Eng.* 2017, 162, 124–139. [[CrossRef](#)]
- [15] Astolfi, P.; Gabrielli, A.; Bascetta, L.; Matteucci, M. Vineyard autonomous navigation in the Echord++ GRAPE experiment. *IFAC-PapersOnLine* 2018, 51, 704–709. [[CrossRef](#)]
- [16] Ahmadi, Alireza, et al. "Visual Servoing-based Navigation for Monitoring Row-Crop Fields." *arXiv preprint arXiv:1909.12754* (2019).
- [17] <http://vinbot.eu/>
- [18] R Shamshiri, Redmond, et al. "Simulation software and virtual environments for acceleration of agricultural robotics: Features highlights and performance comparison." (2018).
- [19] Kocsis, Mihai, Johannes Buyer, and Raoul Zollner. "A modular and scalable simulation framework for agricultural vehicles." *2016 IEEE/SICE International Symposium on System Integration (SII)*. IEEE, 2016.



- [20] Tsolakis, Naoum, Dimitrios Bechtsis, and Dionysis Bochtis. "AgROS: A Robot Operating System Based Emulation Tool for Agricultural Robotics." *Agronomy* 9.7 (2019): 403.
- [21] <https://www.unrealengine.com/>
- [22] <https://www.farming-simulator.com/>
- [23] Biber, Peter, et al. "Navigation system of the autonomous agricultural robot BoniRob." *Workshop on Agricultural Robotics: Enabling Safe, Efficient, and Affordable Robots for Food Production (Collocated with IROS 2012), Vilamoura, Portugal*. 2012.
- [24] English, A., Ross, P., Ball, D., & Corke, P. (2014, May). Vision based guidance for robot navigation in agriculture. In *2014 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 1693-1698). IEEE.
- [25] Ahmadi, Alireza, et al. "Visual Servoing-based Navigation for Monitoring Row-Crop Fields." *arXiv preprint arXiv:1909.12754* (2019).
- [26] Harik, El Houssein Chouaib, and Audun Korsæth. "Combining hector slam and artificial potential field for autonomous navigation inside a greenhouse." *Robotics* 7.2 (2018): 22.
- [27] Roure, F., Moreno, G., Soler, M., Faconti, D., Serrano, D., Astolfi, P., ... & Matteucci, M. (2017, November). GRAPE: ground robot for vineyard monitoring and protection. In *Iberian Robotics Conference* (pp. 249-260). Springer, Cham.
- [28] Barth, R, Baur, J, Buschmann, T, Edan, Y, Hellström, T, Nguyen, T, Ringdahl, O, Saeys, W, Salinas, C & Vitzrabin, R 2014, Using ROS for agricultural robotics - design considerations and experiences. in Proceedings of the Second International Conference on Robotics and associated High-technologies and equipment for agriculture and forestry. pp. 509-518, RHEA2014, Madrid, Spain, 21/05/14.
- [29] <http://rosagriculture.org/>
- [30] <https://discourse.ros.org/c/ros-agriculture/63>
- [31] Xiong, Ya & Ge, Yuanyue & Grimstad, Lars & From, Pål. (2019). An autonomous strawberry-harvesting robot: Design, development, integration, and field evaluation. *Journal of Field Robotics*. 10.1002/rob.21889.
- [32] <https://spectrum.ieee.org/autaton/robotics/industrial-robots/bosch-deepfield-robotics-weed-control>
- [33] <https://thtechnology.co.uk/>
- [34] Baillie CP, Thomasson JA, Lobsey CR, McCarthy CL, Antille DL. A review of the state of the art in agricultural automation. Part I: Sensing technologies for optimization of machine operation and farm inputs. American Society of Agricultural and Biological Engineers, Annual International Meeting 2018.
- [35] <https://www.iso.org/standard/57556.html>
- [36] Quigley, Morgan, et al. "ROS: an open-source Robot Operating System." *ICRA workshop on open source software*. Vol. 3. No. 3.2. 2009.
- [37] Quigley, Morgan, Brian Gerkey, and William D. Smart. *Programming Robots with ROS: a practical introduction to the Robot Operating System*. "O'Reilly Media, Inc.", 2015.



- [38] Koubâa, Anis, ed. *Robot Operating System (ROS)*. Verlag: Springer, 2017.
- [39] Guimarães, Rodrigo Longhi, et al. "ROS navigation: Concepts and tutorial." *Robot Operating System (ROS)*. Springer, Cham, 2016. 121-160.
- [40] Wang, Z., Gong, L., Chen, Q., Li, Y., Liu, C., & Huang, Y. (2016, August). Rapid developing the simulation and control systems for a multifunctional autonomous agricultural robot with ROS. In *International Conference on Intelligent Robotics and Applications* (pp. 26-39). Springer, Cham.
- [41] Hajjaj, Sami Salama Hussien, and Khairul Salleh Mohamed Sahari. "Bringing ROS to agriculture automation: hardware abstraction of agriculture machinery." *International Journal of Applied Engineering Research* 12.3 (2017): 311-316.
- [42] Post, Mark A., Alessandro Bianco, and Xiu T. Yan. "Autonomous navigation with ROS for a mobile robot in agricultural fields." *14th International Conference on Informatics in Control, Automation and Robotics (ICINCO)*. 2017.
- [43] <http://frobomind.org/>
- [44] Khairuddin, Alif Ridzuan, Mohamad Shukor Talib, and Habibollah Haron. "Review on simultaneous localization and mapping (SLAM)." *2015 IEEE International Conference on Control System, Computing and Engineering (ICCSCE)*. IEEE, 2015.
- [45] Chahine, Georges, and Cédric Pradalier. "Survey of monocular SLAM algorithms in natural environments." *2018 15th Conference on Computer and Robot Vision (CRV)*. IEEE, 2018.
- [46] Fuentes-Pacheco, Jorge, José Ruiz-Ascencio, and Juan Manuel Rendón-Mancha. "Visual simultaneous localization and mapping: a survey." *Artificial intelligence review* 43.1 (2015): 55-81.
- [47] <https://pointclouds.org/>
- [48] Rusu, Radu Bogdan, and Steve Cousins. "3d is here: Point cloud library (pcl)." *2011 IEEE international conference on robotics and automation*. IEEE, 2011.
- [49] Barnea, Ehud, Rotem Mairon, and Ohad Ben-Shahar. "Colour-agnostic shape-based 3D fruit detection for crop harvesting robots." *Biosystems Engineering* 146 (2016): 57-70.
- [50] Barth, Ruud, Jochen Hemming, and Eldert J. van Henten. "Design of an eye-in-hand sensing and servo control framework for harvesting robotics in dense vegetation." *biosystems engineering* 146 (2016): 71-84.
- [51] Sa, I., Lehnert, C., English, A., McCool, C., Dayoub, F., Upcroft, B., & Perez, T. (2017). Peduncle detection of sweet pepper for autonomous crop harvesting—Combined Color and 3-D Information. *IEEE Robotics and Automation Letters*, 2(2), 765-772.
- [52] Nurmaini, Siti, and Bambang Tutuko. "Intelligent Robotics Navigation System: Problems, Methods, and Algorithm." *International Journal of Electrical & Computer Engineering (2088-8708)* 7.6 (2017).1
- [53] Li, Nan, et al. "Review of Machine-Vision-Based Plant Detection Technologies for Robotic Weeding." *2019 IEEE International Conference on Robotics and Biomimetics (ROBIO)*. IEEE, 2019.
- [54] Fountas, S., Mylonas, N., Malounas, I., Rodias, E., Hellmann Santos, C., & Pekkeriet, E. (2020). Agricultural Robotics for Field Operations. *Sensors*, 20(9), 2672.

- [55] Wu, Xiaolong, Stéphanie Aravecchia, and Cédric Pradalier. "Design and implementation of computer vision based in-row weeding system." *2019 International Conference on Robotics and Automation (ICRA)*. IEEE, 2019.
- [56] Wu, X., Aravecchia, S., Lottes, P., Stachniss, C., & Pradalier, C. (2020). Robotic weed control using automated weed and crop classification. *Journal of Field Robotics*, 37(2), 322-340.
- [57] Bangert, W., Kielhorn, A., Rahe, F., Albert, A., Biber, P., Grzonka, S., ... & Kinski, D. (2013). Field-robot-based agriculture: "RemoteFarming. 1" and "BoniRob-Apps". *VDI-Berichte*, 2193(439-446), 2.
- [58] Scholz, Christian, Maik Kohlbrecher, and Arno Ruckelshausen. "Camera-based selective weed control application module ("Precision Spraying App") for the autonomous field robot platform BoniRob." *International Conference of Agricultural Engineering, Zurich*. 2014.
- [59] Derby, Stephen, and Christine Connolly. "ABB high-speed picking robots establish themselves in food packaging." *Industrial Robot: An International Journal* (2007).
- [60] Pierrot, François, C. Reynaud, and Alain Fournier. "DELTA: a simple and efficient parallel robot." *Robotica* 8.2 (1990): 105-109.
- [61] <https://www.sigmacontrol.eu/producten-sigmacontrol/delta-robot>
- [62] <https://industrial.omron.nl/nl/products/x-delta-3+1>
- [63] Huo, Feng, GeokSoon Hong, and AunNeow Poo. "Extended development of LinuxCNC for control of a Delta robot." *2015 International Conference on Advanced Mechatronic Systems (ICAMechS)*. IEEE, 2015.
- [64] Arrazate, Rodrigo Torres. "Development of a URDF file for simulation and programming of a delta robot using ROS." (2017).
- [65] <https://www.fanuc.eu/be/en/robots/robot-filter-page/lrmate-series>
- [66] <https://www.universal-robots.com/>
- [67] <https://www.franka.de/technology>
- [68] <https://www.kinovarobotics.com/en>
- [69] Adamchuk, V. I., Rossel, R. V., Sudduth, K. A., & Lammers, P. S. (2011). Sensor fusion for precision agriculture. *Sensor Fusion-Foundation and Applications. InTech, Rijeka, Croatia*, 27-40.
- [70] Bulanon, Duke M., Thomas F. Burks, and Victor Alchanatis. "A multispectral imaging analysis for enhancing citrus fruit detection." *Environmental Control in Biology* 48.2 (2010): 81-91.
- [71] Sa, I., Popović, M., Khanna, R., Chen, Z., Lottes, P., Liebisch, F., ... & Siegwart, R. (2018). Weedmap: a large-scale semantic weed mapping framework using aerial multispectral imaging and deep neural network for precision farming. *Remote Sensing*, 10(9), 1423.
- [72] Slaughter, D. C., Giles, D. K., Fennimore, S. A., & Smith, R. F. (2008). Multispectral machine vision identification of lettuce and weed seedlings for automated weed control. *Weed Technology*, 22(2), 378-384.
- [73] Kusumam, K., Krajník, T., Pearson, S., Duckett, T., & Cielniak, G. (2017). 3D-vision based detection, localization, and sizing of broccoli heads in the field. *Journal of Field Robotics*, 34(8), 1505-1518.
- [74] Lehnert, C., English, A., McCool, C., Tow, A. W., & Perez, T. (2017). Autonomous sweet pepper harvesting for protected cropping systems. *IEEE Robotics and Automation Letters*, 2(2), 872-879.

- [75] Bakker, T. (2009). *An autonomous robot for weed control: design, navigation and control*.
- [76] Kamilaris, Andreas, and Francesc X. Prenafeta-Boldú. "Deep learning in agriculture: A survey." *Computers and electronics in agriculture* 147 (2018): 70-90.
- [77] Van Henten, E. J., Hemming, J., Van Tuijl, B. A. J., Kornet, J. G., & Bontsema, J. (2003). Collision-free motion planning for a cucumber picking robot. *Biosystems Engineering*, 86(2), 135-144.
- [78] Strisciuglio, N., Tylecek, R., Blaich, M., Petkov, N., Biber, P., Hemming, J., ... & Brox, T. (2018, June). Trimbot2020: an outdoor robot for automatic gardening. In *ISR 2018; 50th International Symposium on Robotics* (pp. 1-6). VDE.
- [79] Zhang, Baohua, and Jun Zhou. "Introductory Chapter: Recent Development and Applications of Agricultural Robots." *Agricultural Robots-Fundamentals and Applications*. IntechOpen, 2018.
- [80] Jia, B., Zhu, A., Yang, S. X., & Mittal, G. S. (2009, December). Integrated gripper and cutter in a mobile robotic system for harvesting greenhouse products. In *2009 IEEE International Conference on Robotics and Biomimetics (ROBIO)* (pp. 1778-1783). IEEE.
- [81] Setiawan, Achmad Irwan, Tomonari Furukawa, and Adam Preston. "A low-cost gripper for an apple picking robot." *IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA'04. 2004*. Vol. 5. IEEE, 2004.
- [82] Laliberte, Thierry, Lionel Birglen, and Clement Gosselin. "Underactuation in robotic grasping hands." *Machine Intelligence & Robotic Control* 4.3 (2002): 1-11.
- [83] Russo, M., Ceccarelli, M., Corves, B., Hüsing, M., Lorenz, M., Cafolla, D., & Carbone, G. (2017). Design and test of a gripper prototype for culture products. *Robotics and Computer-Integrated Manufacturing*, 44, 266-275.
- [84] Ma, Raymond, and Aaron Dollar. "Yale openhand project: Optimizing open-source hand designs for ease of fabrication and adoption." *IEEE Robotics & Automation Magazine* 24.1 (2017): 32-40.
- [85] McCool, C., Sa, I., Dayoub, F., Lehnert, C., Perez, T., & Upcroft, B. (2016, May). Visual detection of occluded crop: For automated harvesting. In *2016 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 2506-2512). IEEE.
- [86] Sa, I., Lehnert, C., English, A., McCool, C., Dayoub, F., Upcroft, B., & Perez, T. (2017). Peduncle detection of sweet pepper for autonomous crop harvesting—Combined Color and 3-D Information. *IEEE Robotics and Automation Letters*, 2(2), 765-772.
- [87] Barnea, Ehud, Rotem Mairon, and Ohad Ben-Shahar. "Colour-agnostic shape-based 3D fruit detection for crop harvesting robots." *Biosystems Engineering* 146 (2016): 57-70.
- [88] Gongal, A., Amatya, S., Karkee, M., Zhang, Q., & Lewis, K. (2015). Sensors and systems for fruit detection and localization: A review. *Computers and Electronics in Agriculture*, 116, 8-19.
- [89] Lehnert, C., Sa, I., McCool, C., Upcroft, B., & Perez, T. (2016, May). Sweet pepper pose detection and grasping for automated crop harvesting. In *2016 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 2428-2434). IEEE.
- [90] Bergamini, L., Sposato, M., Pellicciari, M., Peruzzini, M., Calderara, S., & Schmidt, J. (2020). Deep learning-based method for vision-guided robotic grasping of unknown objects. *Advanced Engineering Informatics*, 44, 101052.
- [91] Bousmalis, K., Irpan, A., Wohlhart, P., Bai, Y., Kelcey, M., Kalakrishnan, M., ... & Levine, S. (2018, May). Using simulation and domain adaptation to improve efficiency of deep robotic

grasping. In *2018 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 4243-4250). IEEE.

[92] Caldera, S., Rassau, A., & Chai, D. (2018). Review of deep learning methods in robotic grasp detection. *Multimodal Technologies and Interaction*, 2(3), 57.

[93] Lenz, Ian, Honglak Lee, and Ashutosh Saxena. "Deep learning for detecting robotic grasps." *The International Journal of Robotics Research* 34.4-5 (2015): 705-724.

[94] Depierre, A., Dellandréa, E., & Chen, L. (2018, October). Jacquard: A large scale dataset for robotic grasp detection. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 3511-3516). IEEE.

[95] Wang, S., Jiang, X., Zhao, J., Wang, X., Zhou, W., & Liu, Y. (2019). Efficient Fully Convolution Neural Network for Generating Pixel Wise Robotic Grasps With High Resolution Images. *arXiv preprint arXiv:1902.08950*.

[96] Dörr, J., Fairclough, B., Henningsen, J., Jahić, J., Kersting, S., Mennig, P., ... & Scholten-Buschhoff, F. (2019). Scouting the Autonomous Agricultural Machinery Market.

[97] <https://www.eu-robotics.net/cms/upload/downloads/ppp-documents/Multi-Annual-Roadmap2020-ICT-24-Rev-B-full.pdf>

[98] <https://www.fira-agtech.com/en/>

[99] <https://roscon.ros.org/>

[100] <https://waset.org/agricultural-robotics-automation-and-control-conference>

<http://ieeagra.com/>

[101] <http://rosagriculture.org/>

[102] <https://opencv.org/>

[103] McGlynn, Shavon, and Drew Walters. "Agricultural Robots: Future Trends for Autonomous Farming." (2019). Journal of emerging technologies and innovative research

[104] Kawakura, Shinji, and Ryosuke Shibasaki. "Optical Flow–Based Study Related to Outdoor Tree Pruning Using OpenCV Utilities and Captured Visual Data." *Journal of Advanced Agricultural Technologies Vol 6.1* (2019).

[105] Thakur, S., Bawiskar, S., Singh, S. K., & Shanmugasundaram, M. (2020). Autonomous Farming—Visualization of Image Processing in Agriculture. In *Inventive Communication and Computational Technologies* (pp. 345-351). Springer, Singapore.

[106] Zhang, Q. R., Peng, P., & Jin, Y. M. (2016). Cherry Picking Robot Vision Recognition System Based on OpenCV. In *MATEC Web of Conferences* (Vol. 63, p. 01005). EDP Sciences.

[107] <https://www.tensorflow.org/>

[108] <http://caffe.berkeleyvision.org/>

[109] <https://pytorch.org/>

[110] Habaragamuwa, H., Ogawa, Y., Suzuki, T., Shiigi, T., Ono, M., & Kondo, N. (2018). Detecting greenhouse strawberries (mature and immature), using deep convolutional neural network. *Engineering in Agriculture, Environment and Food*, 11(3), 127–138.

[111] Sa, I., Ge, Z., Dayoub, F., Upcroft, B., Perez, T., & McCool, C. (2016). Deepfruits: A fruit detection system using deep neural networks. *Sensors*, 16(8), 1222.

- [112] Xiong, Y., Ge, Y., Grimstad, L., & From, P. J. (2020). An autonomous strawberry-harvesting robot: Design, development, integration, and field evaluation. *Journal of Field Robotics*, 37(2), 202-224.
- [113] <https://tldrlegal.com>
- [114] <https://choosealicense.com>
- [115] <https://opensource.org/licenses>
- [116] Nadan, Christian H. "Open source licensing: Virus or virtue." *Tex. Intell. Prop. LJ* 10 (2001): 349.
- [117] SAE International. Automated Driving - Levels of Driving Automation are Defined in New SAE International Standard J3016 2014
- [118] Koopman P. An Overview of Draft UL 4600: Standard for Safety for the Evaluation of Autonomous Products. [October 22, 2019]; Available from: https://medium.com/@pr_97195/an-overview-of-draftul-4600-standard-for-safety-for-the-evaluation-of-autonomousproducts-a50083762591
- [119] ISO-Standard. ISO/PAS 21448:2019 Road vehicles — Safety of the intended functionality. [October 21, 2019]; Available from: <https://www.iso.org/standard/70939.html>
- [120] Devitt, S. Kate. "Cognitive factors that affect the adoption of autonomous agriculture." *Farm Policy Journal* 15.2 (2018): 49-60.
- [121] <http://wiki.ros.org/Sensors>
- [122] Hajjaj, S. S. H., & Sahari, K. S. M. (2016, December). Review of agriculture robotics: Practicality and feasibility. In *2016 IEEE International Symposium on Robotics and Intelligent Sensors (IRIS)* (pp. 194-198). IEEE.
- [123] https://docs.google.com/document/d/12vNr4J_F6usQ6ok8n0j65PO8CPHlxqs29oNj9h0Xz4Q/edit#
- [124] <https://farm.bot/>
- [125] <https://agopengps.jimdosite.com/>, <https://agopengps.discourse.group/>
- [126] Redenius, J., Belau, S., Irmer, D., Ruckelshausen, A., Middelberg, R., Spiekermann, S., ... & Hertzberg, J. 'Virtual Harvesting' as a Key Element in the Development of a novel LiDAR based Combine Harvester Steering System.
- [127] Kelber, C. R., Reis, B. R., & Figueiredo, R. M. (2016, November). Improving functional safety in autonomous guided agricultural self propelled machines using hardware-in-the-loop (HIL) systems for software validation. In *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)* (pp. 1438-1444). IEEE.
- [128] Özçelikörs, Mustafa. "A Comparative Overview of Robotic Frameworks: ROS and RSB."
- [129] Ahmad, Aakash, and Muhammad Ali Babar. "Software architectures for robotic systems: A systematic mapping study." *Journal of Systems and Software* 122 (2016): 16-39.
- [130] <https://www.mrpt.org/>
- [131] <https://ompl.kavrakilab.org/>
- [132] <https://moveit.ros.org/>
- [133] <http://openrave.org/>

- [134] <https://www.zephyrproject.org/>
- [135] Shamshiri, R., & Ismail, W.I. (2013). Design and Simulation of Control Systems for a Field Survey Mobile Robot Platform. Research Journal of Applied Sciences, Engineering and Technology, 6, 2307-2315.
- [136] T. Blender, T. Buchner, B. Fernandez, B. Pichlmaier and C. Schlegel, "Managing a Mobile Agricultural Robot Swarm for a seeding task," IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, 2016, pp. 6879-6886, doi: 10.1109/IECON.2016.7793638.
- [137] Tarazón, R.L.. (2015). Robotics in Micro-manufacturing and Micro-robotics. 10.1016/B978-0-323-31149-6.00028-1.
- [138] <http://navigation.ros.org>
- [139] Fue, K.G.; Porter, W.M.; Barnes, E.M.; Rains, G.C. An Extensive Review of Mobile Agricultural Robotics for Field Operations: Focus on Cotton Harvesting. AgriEngineering 2020, 2, 150-174.
- [140] <https://tldrlegal.com/>
- [141] S.S. Mehta, W. MacKunis, and T.F. Burks. 2016. Robust visual servo control in the presence of fruit motion for robotic citrus harvesting. Comput. Electron. Agric. 123, C (April 2016), 362–375.
- [142] <https://research.qut.edu.au/future-farming/projects/robot-platform-design-agbot-ii-a-new-generation-tool-for-robotic-site-specific-crop-and-weed-management/>
- [143] Wallace, Nathan D. et al. "Experimental validation of structured receding horizon estimation and control for mobile ground robot slip compensation." (2019).
- [144] Jørgensen, Rasmus Nyholm et al. "HortiBot: A System Design of a Robotic Tool Carrier for High-tech Plant Nursing." (2007).
- [145] Stein M, Bargoti S, Underwood J. Image Based Mango Fruit Detection, Localisation and Yield Estimation Using Multiple View Geometry. Sensors (Basel). 2016;16(11):1915.
- [146] Underwood, James Patrick et al. "Real-time target detection and steerable spray for vegetable crops." (2015).
- [147] Arad, B, Balendonck, J, Barth, R, et al. Development of a sweet pepper harvesting robot. J Field Robotics. 2020; 1– 13.
- [148] Henten EJvan, Tuijl BAJvan, Hemming J, et al. Field test of an autonomous cucumber picking robot. Biosystems Engineering. 2003 Nov;86(3):305-313.
- [149] Williams, Henry et al. "Robotic kiwifruit harvesting using machine vision, convolutional neural networks, and robotic arms." Biosystems Engineering 181 (2019): 140-156.
- [150] Zhao, Yuanshen & Gong, Liang & Liu, Chengliang & Huang, Yixiang. (2016). Dual-arm Robot Design and Testing for Harvesting Tomato in Greenhouse. IFAC-PapersOnLine. 49. 161-165.
- [151] Qingchun, Feng & Zou, Wei & Fan, Pengfei & Zhang, Chunfeng & Wang, Xiu. (2018). Design and test of robotic harvesting system for cherry tomato. International Journal of Agricultural and Biological Engineering. 11. 96-100.
- [152] <https://news.panasonic.com/global/stories/2018/57801.html>. Accessed on May 23, 2018.

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